Accurate Lumen Segmentation and Stenosis Detection and Quantification in Coronary CTA

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Abstract. Accurate detection and quantification of coronary artery stenoses is fundamental in correct patient diagnosis and optimal treatment planning. Central to detection and quantification is the correct estimation of lumen in the coronary vessel. Here, we describe a method for accurate lumen segmentation in CTA and present results of an early prototype for stenosis detection and quantification for a variety of datasets. For the detection, a sensitivity of 72% and a PPV of 17% is obtained as compared to QCA, while a sensitivity of 57% and a PPV of 18% is achieved as compared to CTA. The stenosis degree is estimated with an absolute average difference of 49% as compared to QCA, and a weighted kappa value of -0.15 is obtained as compared to CTA. A Dice of 73% and 69% is reported for lumen segmentation of healthy and diseased vessel segments respectively.

Keywords: stenosis, segmentation, coronary

1 Introduction

Narrowing of the coronary arteries (stenosis) has a dramatic effect on blood pressure, resistance and blood flow. Resistance increases when radius decreases, as friction of blood flow against vessel wall increases. Therefore the circulation of blood flow is reduced, and cells may be deprived of oxygen or experience toxic accumulation of metabolic wastes. Accurate stenosis detection is therefore crucial in patient diagnosis. Furthermore the accurate determination of the degree of stenosis is important as it is fundamental in deciding treatment strategies.

Since stenosis is usually defined as a reduction of the free flowing lumen diameter over what's to be expected in a normal vessel, it follows that correct lumen segmentation is of the essence.

1.1 Previous Work

There is a substantial volume of literature on coronary artery segmentation. This becomes even larger when looking at vascular segmentation in general, given that many techniques that have been applied for other vessels can easily be used for coronaries. Compounding that, a lot of techniques reported for MRA vessel segmentation can also be used for CTA. We will, therefore, only attempt a

cursory review of previously reported work. For a more comprehensive analysis and categorization of vessel segmentation techniques, the reader is directed to [1] and [2]

Wang et. al. [3] employ a dual-snake approach to simultaneously detect the inner and outer wall borders. Grosskopf et. al. iteratively utilize a 3D Active Contour Model (ACM) with refinements on Multi-Planar Reconstructions (MPRs) using 2D ACMs [4]. In [5] Rink et. al. present a shape-based segmentation and visualization technique using two surface representations, one for the contrast filled vessel lumen and also one for the vascular wall.

Bock et. al. [6] propose a progressive region growing approach with a growth front monitoring technique to control the segmentation and correct local leakage by retrospective detection and removal of leakage artifacts. In [7], Renard et al. perform lumen segmentation by adaptive region growing, computing local statistics for the appearance of lumen voxels.

In [8], Yang et. al. propose a hybrid approach for segmentation of coronary arteries using multi-scale vessel filtering and a Bayesian probabilistic approach in a level set image segmentation framework. The same group in [9] propose an alternative method where the level set starts at the ostia and operates on a binary volume, where the active voxels are only the ones representing blood. In [10] Nain et.al. propose a level-set method combining an adaptive intensity model with a shape prior model and shape observations on a scale larger than a derivative would look at (i.e. not curvature).

In [11], Fahmi et. al. propose an edge-based level set segmentation technique applied only on the image portion consisting of the voxels that lie within a radius R from the vessel centerline. Xu et. al. [12] propose a method for detecting and quantifying coronary arterial stenosis in CTA using a Fuzzy Distance Transform (FDT) approach. Coronary arterial stenoses are detected and their severities are quantified by analysing FDT values along the medial axis of an artery obtained by skeletonization.

2 Methodology

The key to accurate stenosis detection and quantification is precise lumen segmentation. In our case, we start with the vessel centerline as an input to our algorithm. The process then follows four major steps:

1. Initialization
2. Tissue classification and Calcium segmentation
3. Lumen segmentation
4. Stenosis detection and quantification

The first three parts are covered by a pending patent.

2.1 Initialization

In the initialization step a "stacked volume" is constructed from the given centerline. This volume is constructed by resampling the original volume data across

image cut planes generated at one voxel spacing across the centerline and then stacked on top of one another. Use of this stacked volume simplifies the expression of geometric constraints applied to lumen segmentation.

The algorithm then generates an approximate segmentation of the lumen and vessel wall, using a 3D Active Contour aproach, to be used as input to other components. The final results do not strongly depend on the accuracy of this segmentation and the algorithm used here could be easily replaced by a variety of other segmentation algorithms -or even thresholding followed by morphological operations- with equally good results. We will therefore go no deeper into the details of this step.

2.2 Tissue classification and Calcium segmentation

This step is a crucial pre-requisite for the success of the lumen segmentation to follow. It is critical to be able to differentiate between contrasted blood and the vessel wall, in order to accurately segment the lumen.

Intensity values at the low HU range for lumen, however, are overlapping with values that can reasonably be considered as belonging to vessel wall or the various plaque types. It is therefore not possible to utilize a straightforward approach, like thresholding, and a more sophisticated method is required.

Likewise, in the high HU range, it becomes difficult to tell apart lumen voxels from calcified plaque. As calcified plaque is a major contributor to stenoses though, accurate calcium segmentation becomes paramount. Since identifying and removing calcium voxels will make the classification task easier, it is performed first in our method.

Calcium Segmentation Calcified plaque is identified by an intensity threshold above which a voxel is considered to be calcium (within the general region of the vessel). This threshold is determined by an unsupervised classification technique and is unique to each vessel within the data.

The technique uses a measure known as the Bayesian Information Criterion, applied to determine the number of clusters in a given set of data [13]. Assuming the clusters to have Gaussian distributions, the BIC can be written in a closed form as:

$$BIC = \sum_{i=1}^{m}(n_i log n_i - n_i log n - \frac{n_i * d}{2} log(2\pi) - \frac{n_i}{2} log V_i - \frac{n_i - m}{2}) - \frac{1}{2} m log n$$

where V_i is the variance estimate for each cluster, d the number of dimensions, n_i the number of samples in each cluster, and m the number of clusters (in our case 2).

The technique first collates all voxel intensities over a specific HU value within the initial vessel segmentation. (this value is sufficiently high as to include only lumen or potential calcified plaque.) It then iterates over several potential thresholds (starting at the maximum HU value and reducing by a fixed amount in each iteration), partitioning the initial voxel intensities into two clusters.

The BIC is computed for each potential threshold, and the result is plotted against the potential threshold. The best possible threshold to separate the two distributions is the first maximum of the BIC curve (BIC v threshold) in the direction of large to small threshold values [13]. A schematic of the process can be seen in Fig. 1.

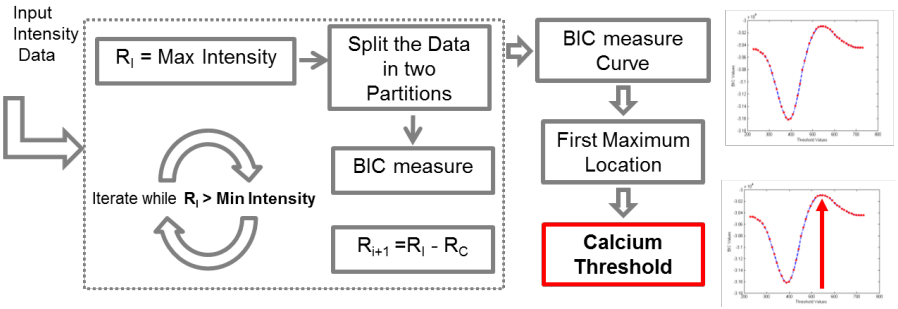

Fig. 1. Calcified Plaque Threshold Estimation

Tissue classification In the tissue classification step we are trying to construct posterior probabilities that a pixel with a given intensity is vessel wall or lumen. These, in turn, will be used later to drive our level-set for lumen segmentation. Voxels identified as calcified plaque by the method described above are excluded.

Using the approximate initial segmentation the vessel is divided into small segments. A kernel is defined over a region consisting of an arbitrary range of segments.(Regions can overlap by an arbitrary amount.) Each region is classified according to the appropriately weighted segment assuming a two class distribution.

Assuming Gaussian distributions for the two tissue classes, wall and lumen, we use k-Means[14,15] followed by Expectation-Maximization[16] to extract mean, variance, and weight of each distribution. Each voxel can then be given probabilities of belonging to the lumen or wall classes according to it's HU value, from the estimated probability distribution functions.

2.3 Lumen Segmentation

Segmentation of the vessel lumen follows a level-set approach. The level-set described by Nilsson [17] is used, primarily for reasons of computation speed. The speed function driving the level-set uses the tissue classification described above, in an approach similar to that described in [9], while the calcium threshold is used to prevent the inclusion of calcified plaque.

2.4 Stenosis detection and quantification

Detecting stenoses is a direct by-product of the lumen segmentation. In this early prototype, stenosis detection and quantification are performed based on estimating the expectated vessel profile at each point along the vessel. Having segmented the lumen we fit a line to the calculated vessel lumen diameters, providing an expectation of the lumen diameter ate each position. The stenosis percentage is then calculated as the percentage deviation of the real lumen diameter from the expected one. Only areas with estimated stenosis higher than 20% are reported.

With this method of using the estimated expected vessel profile, detection and quantification of stenoses is simultaneously achieved. An accurate Lumen Segmentation is, therefore, a key requirement for such a method. It is essential that the lumen segmentation is capturing enough detail so that a stenosed region can be discriminated from a healthy region and accurately quantified.

3 Results

The algorithm has been tried on a set of 24, previously unseen, datasets provided by the organizers of the *3D Cardiovascular Imaging: a MICCAI segmentation challenge* workshop. As our algorithm requires coronary centerlines as input, these were also provided by the organizers. The centerlines provided were estimated by the Rcadia team method, as described in [18].

Evaluation of the algorithm results was performed by the workshop's on-line evaluation framework. Three main categories were looked at, namely:

1. Stenosis Detection
2. Stenosis Quantification
3. Lumen Segmentation

3.1 Stenosis Detection

Detection has been evaluated against reference from two clinically relevant stenosis measures, the CTA and QCA. Only heavy stenoses (i.e. more than 50%) have been considered. So for a reported stenosis to count as detection it must not just be in the correct position, but also be quantified as higher than 50%. This, in effect, skews the pure detection results (i.e. is a reported stenosis in the same place as a true one), but gives a picture of what a physician would be interested to see in a clinical setting. For both CTA and QCA references, sensitivity and positive predictive value are reported and compared with results from three expert observers evaluating the same datasets. The results can be seen in Table 1.

As can be seen, our method achieves good detection rates and compares favourably to human experts for the QCA reference standard. Further work is clearly needed though to increase the Positive Predictive Value of the algorithm and therefore give more confidence in the reported detections. The view taken on this early prototype was to try not to miss a clinically important stenosis, even at the expense of more false positives.

	QCA Sens.	QCA P.P.V	CTA Sens.	CTA P.P.V
Observer1	0.88	0.40	0.77	0.58
Observer2	0.70	0.49	0.64	0.72
Observer3	0.68	0.45	0.68	0.62
Our Result	0.72	0.17	0.57	0.18

Table 1. Stenosis Detection Results vs Observers

3.2 Stenosis Quantification

In quantification, the goal is to evaluate how accurately the degree of a stenosis has been ascertained. The metrics here are the average absolute difference and the R.M.S. difference of the reported QCA values to the real ones and also the Weighted Kappa value for the reported CTA values. The Weighted Kappa is a metric that informs on the chance that a certain grouping of results could agree with the true ones by chance. Results, again against three expert observers, can be seen in Table 2.

	QCA Avg. Abs. Diff.	QCA R.M.S. Diff.	CTA Weighted Kappa
Observer1	30.6	35.7	0.36
Observer2	32.6	37.5	0.34
Observer3	31.0	37.1	0.28
Our Result	49.3	55.8	-0.15

Table 2. Quantification Results vs Observers

3.3 Lumen Segmentation

Lumen segmentations from our algorithm are reported in the form of surface meshes. The metrics used for evaluation in this case are the popular DICE metric and the mean and max surface distances between the reported results and the true ones. Values for these metrics are reported separately for the various diseased and healthy vessel portions, in Table 3. Results for the 24 datasets are presented and again compared with the human expert observers.

	DICE diseased	DICE healthy	MSD diseased	MSD healthy	MAXSD diseased	MAXSD healthy
Observer1	0.76	0.77	0.09	0.18	2.74	3.41
Observer2	0.64	0.72	0.12	0.20	2.83	3.13
Observer3	0.79	0.81	0.08	0.15	2.91	3.27
Our Result	0.69	0.73	0.15	0.31	2.79	2.95

Table 3. Lumen Segmentation Results vs Observers

Results for segmentations show good agreement with the true lumen, with a high dice coefficient and low surface deviations for both healthy and diseased regions. This is a significant result, since detection and quantification critically depend on the segmentation quality, but also in enabling other applications in the clinical coronary workflow.

4 Conclusions

We have presented a method of coronary tissue classification and lumen segmentation and an initial prototype method for stenosis detection and quantification. Our algorithm results in accurate lumen segmentation with a high dice coefficient and low surface deviations for both healthy and diseased regions. Stenosis detection demonstrates good sensitivity, while obviously tuned to reduce the number of false negatives. Regarding stenosis quantification, we did not model QCA from CTA measurements and we do not achieve higher accuracy than the manual expert quantification.

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